Technical Report REMR-CS-58
June 1998

US Army Corps
of Engineers
Waterways Experiment
Station

*Repair, Evaluation, Maintenance, and Rehabilitation Research Program*

# Application of Artificial Neural Networks to Ultrasonic Pulse Echo System for Detecting Microcracks in Concrete

*by A. Michel Alexander, Richard W. Haskins*

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Prepared for Headquarters, U.S. Army Corps of Engineers

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| | Problem Area | | Problem Area |
|---|---|---|---|
| CS | Concrete and Steel Structures | EM | Electrical and Mechanical |
| GT | Geotechnical | EI | Environmental Impacts |
| HY | Hydraulics | OM | Operations Management |
| CO | Coastal | | |

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3909 Halls Ferry Road
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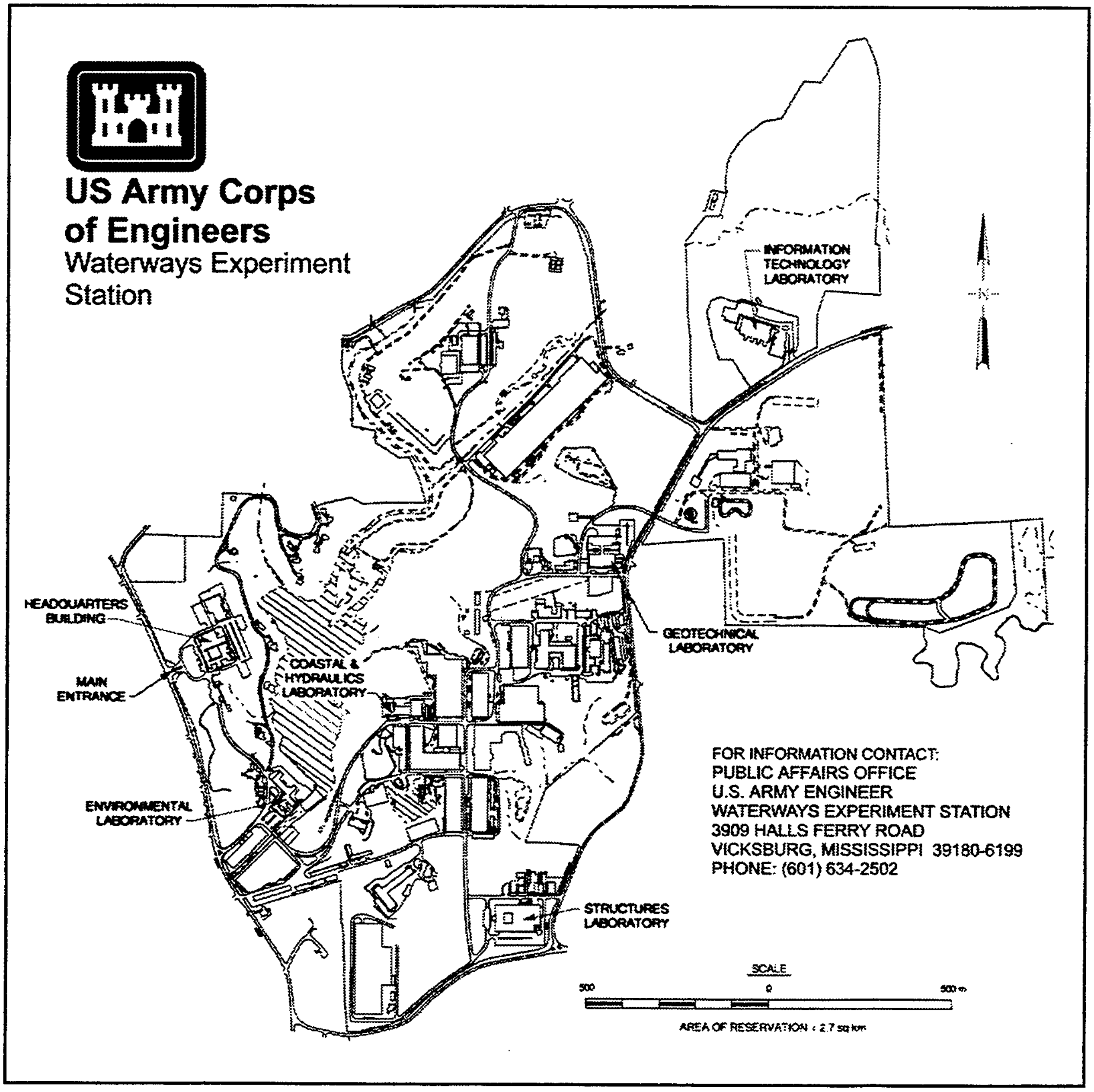


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# Contents

# List of Figures

# Preface

The work described in this report was authorized by Headquarters, U.S. Army Corps of Engineers (HQUSACE), as part of the Concrete and Steel Structures Problem Area of the Repair, Evaluation, Maintenance, and Rehabilitation (REMR) Research Program. The work was performed under Work Unit 32638, "Nondestructive Evaluation Systems for Civil Works Structures." Mr. M. K. Lee, CECW-EG, was the REMR Technical Monitor for this work.

Dr. Tony C. Liu, CERD-C, was the REMR Coordinator at the Directorate of Research and Development, HQUSACE. Mr. Harold C. Tohlen, CECW-O, and Dr. Liu served as the REMR Overview Committee. Mr. William F. McCleese, Concrete and Materials Division (CMD), Structures Laboratory (SL), U.S. Army Engineer Waterways Experiment Station (WES), was the REMR Program Manager. Mr. James E. McDonald, CMD, was the Problem Area Leader. Mr. A. Michel Alexander, CMD, was the Principal Investigator.

The work was performed at WES, and this report was prepared by Mr. Alexander and Mr. Richard W. Haskins, Information Technology Laboratory, WES, under the general supervision of Dr. Bryant Mather, Director, SL, and Mr. John Q. Ehrgott, Assistant Director, SL, and under the direct supervision of Dr. Paul Mlakar, Chief, CMD. Dr. Toy Poole and Mr. John Cook, Engineering Sciences Branch, CMD, assisted in development of an optimum mechanism for engineering cracks in concrete.

At the time of the publication of this report, Dr. Robert W. Whalin was Director of WES. The Commander was COL Robin R. Cababa, EN.

# 1 Introduction

## Background

Considerable engineering judgment is needed for an operator to interpret the quality of concrete from the signals of ultrasonic pulse echo (UPE) measurements. Literally thousands of slightly different UPE signals can be obtained from various concretes. Personnel may need years of training to recognize and identify the complicated signal patterns in the pulse echo technologies of ultrasonics and radar. Automating the interpretation process would reduce the dependency on the judgment of highly trained personnel and would improve the consistency of the decision-making process. A computerized system such as the artificial neural network (ANN) should be used for performing objective signal interpretations so that the subjective decisions of various operators are reduced or eliminated.

An ANN system is a mathematical technique that can make intelligent decisions automatically by means of a computer. ANNs imitate human brain behavior in the way they perform tasks. The idea of a network of neurons, or separate computational elements, working collectively to perform complex tasks dates back to Hebb (1949). In the 1980s, ANNs were developed that could distinguish voices and faces (Windsor et al. 1993). ANN algorithms can be trained to recognize certain signal features using known examples; then the trained ANN can be applied to an unknown but similar problem to interpret those signal features. Specific examples can be fed to the ANN, and it can generalize to learn the whole as long as the specific examples are a representation of the whole. In other words, unseen signals that the ANN has not encountered in training can be properly classified by the ANN as long as the data used to train the ANN have similar characteristics as the unseen data.

One benefit of the ANN is the fact that it is not necessary to program an algorithm or set of rules for processing the raw signal as is necessary with conventional computer programs. One does not have to know the relationship (mathematical function that relates the independent variables to the dependent variable) between electrical features of the UPE signal and the physical condition of the concrete. The ANN has adaptive capabilities that permit it to discover relationships among variables when first trained with known examples. In addition to the ability to generalize, ANN algorithms can (a) be implemented in

parallel for real-time answers, (b) relate nonlinear multiple variables, (c) handle noise in the signals, and (d) handle great variability in a magnitude of inputs. Furthermore, ANN algorithms do not require a mathematical function to relate variables. As stated by Taha and Hanna (1995), "Neural Networks are attracting an enormous amount of attention in many Civil Engineering disciplines...because they represent a class of robust, non-linear models capable of learning relationships from data." This method is referred to as *neurocomputing* as opposed to the very familiar technique to all engineers of *programmed computing* (Hecht-Nielsen 1989).

An ANN can be trained so that the computer can classify the UPE signals from concrete of known quality/deterioration and then interpret UPE signals on concrete of unknown quality. Then only a minimum level of training will be necessary for operators to perform UPE measurements on concrete structures and diagnose the condition of the material. Consistent objective decisions can then be made by the computer rather than the subjective decisions of various human operators. A trained ANN offers the potential of a successful on-line, real-time, flaw-detection system for concrete capable of operating at high speeds (Windsor et al. 1993).

## Objective

The objective of this investigation was to determine the feasibility of using the ANN to automate the interpretation of UPE signals made from concrete possessing deterioration of the continuous-interface type.

## Scope of Report

Chapter 2 of this report describes a laboratory prototype UPE system developed at the U.S. Army Engineer Waterways Experiment Station (WES) and defines two categories of crack defects in concrete. Chapter 3 explains the procedures for engineering microcracks in specimens. Chapter 4 explains the process for rating the degree of microcracking and for collecting UPE training data. Chapter 5 describes the architecture of the ANN and its application to UPE data. Chapter 6 contains conclusions and recommendations derived from this investigation.

# 2 Laboratory Prototype UPE System

UPE systems are important diagnostic tools when only one concrete surface is accessible for the measurement. In 1986, a high-resolution laboratory UPE system for detecting defects in concrete (Figure 1) was developed at WES under the Repair, Evaluation, Maintenance, and Rehabilitation (REMR) Research Program (Thornton and Alexander 1987). The transmitter is a low quality factor (Q) piezoelectric array composed of lead metaniobate elements. The center frequency operates at about 190 kHz. The bandwidth contains energy from below 50 kHz to just over 350 kHz. The pulse length is short, only two and one-half to three cycles, which is critical for UPE systems (an ultrasonic pulse velocity (UPV) system can have a pulse length of 50 to 100 cycles since the time-of-arrival (TOA) of the first cycle is the only important criterion). The receiver is a commercial unit, Panametrics Model A301S, which also has a low Q and is resonant at 0.5 MHZ. The receiver operates in the broadband portion of its frequency spectrum curve at frequencies below resonance. The pair of transmitting and receiving transducers are shown in Figure 2. More information on the UPE system and a history of UPE development in concrete are given in Alexander and Thornton (1988).

Although the operation of the ultrasonic hardware is acceptable and the needed information about the quality/deterioration of the concrete is likely contained in the UPE signals, it is not a straightforward problem to interpret the condition of the concrete from those signals. Crack defects can generally be divided into two categories: those that have discrete interfaces and those that have continuous interfaces.

## Interpretation of UPE Signals from Discrete Interfaces

WES staff members have performed studies to develop measurement criteria for detecting discrete interfaces in concrete using the UPE system. Although some digital signal processing algorithms are used to help interpret the signals, all of the evaluation must be performed manually. Discrete interfaces are present

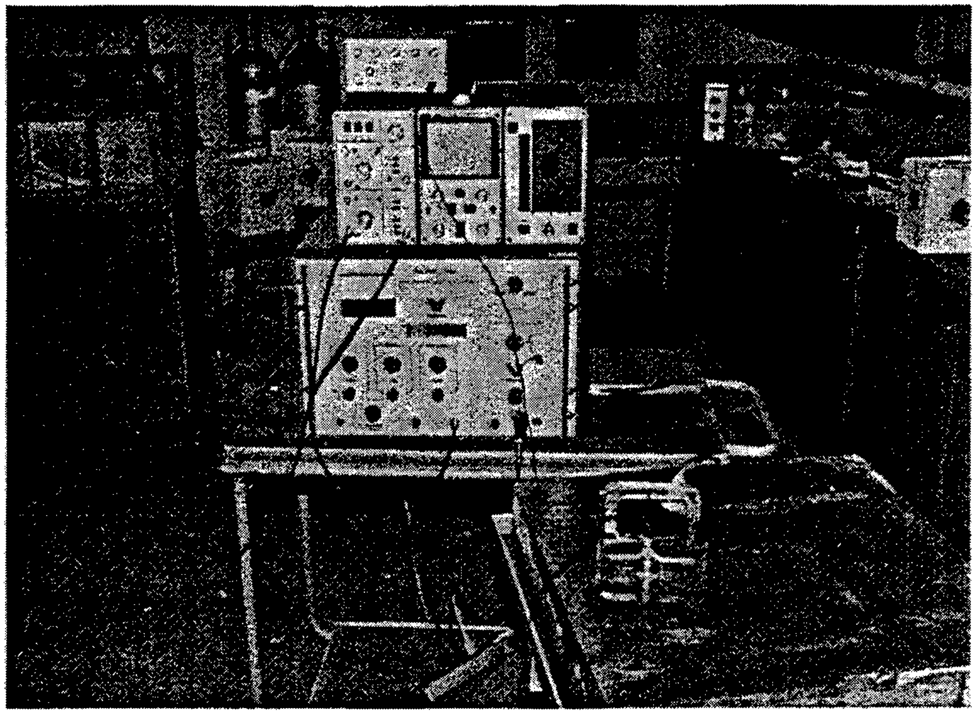

Figure 1. Laboratory UPE system

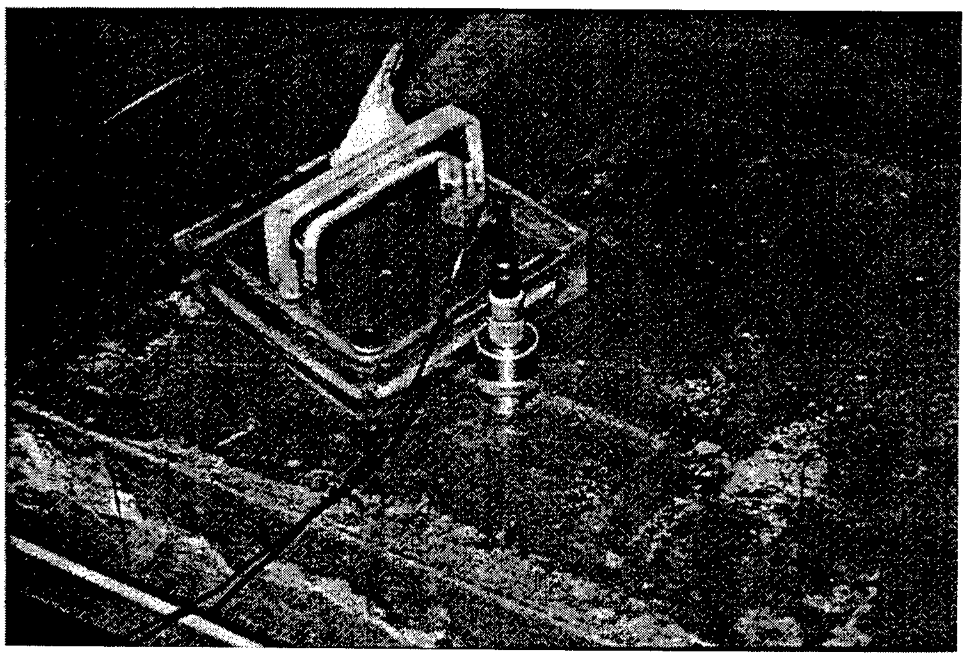

Figure 2. Close-up of UPE transducers

when detecting embedded steel, measuring thicknesses of various elements, and detecting voids, delaminations, and embedded objects, etc. TOAs of echoes from discrete interfaces occur at definite locations in the signal as evidenced by the sharp transitions of amplitude that occur when an echo is received. Currently, various algorithms exist that will permit researchers to improve the use of the computer for locating and displaying (interpret) discrete echoes in the signal. Figure 3 shows the type of UPE signal that the system records when the concrete is sound. The TOA of the backwall echo is about 106 μsec for this particular concrete element, 235 mm (9.25 in.) in thickness. A discrete interface, such as the example shown, will return one primary echo at a definite TOA.

## Interpretations of Signals from Continuous Interfaces

For deterioration of the type caused by alkali-silica reaction, fire damage, freeze and thaw damage, etc., the interfaces are continuous rather than discrete. Measurement criteria have not been developed for correlating the electrical features of the signals with the physical features of deterioration in the concrete. Thousands of microcracks with random lengths, widths, positions, and directions can exist. This type of amorphous deterioration can return a multitude of interfering echoes rather than the less complicated discrete echoes seen from reinforcement bars and backwall surfaces as shown in Figure 3. In Figure 4, a typical UPE signal is recorded from the measurement of a microcracked specimen. As can be seen, there are many interfering echoes arriving at all TOAs for continuous interfaces. Note that the reflected energy is spread throughout the time-domain signal in the case of continuous interfaces, and the reflected energy is located at discrete TOAs for signals from discrete interfaces. To develop measurement criteria, it is necessary to build a specimen library of uniformly cracked specimens for which the type and magnitude of the cracks are known. The ANN is ideally suited for this type of problem because a mathematical procedure or algorithm does not have to exist for relating signal features to physical features in the concrete.

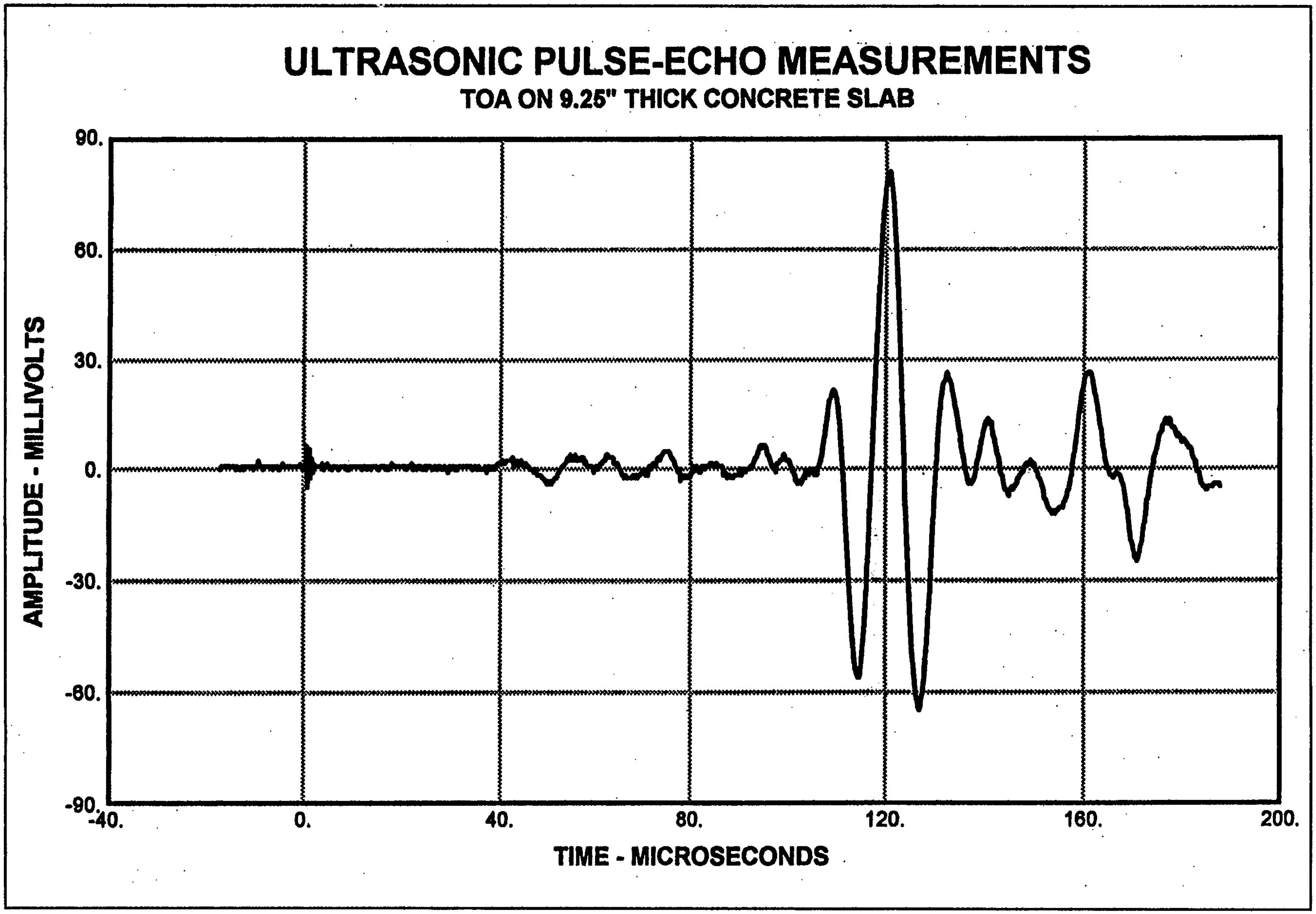


Figure 3. UPE measurement from a discrete interface (234.9 mm (9.25 in.))

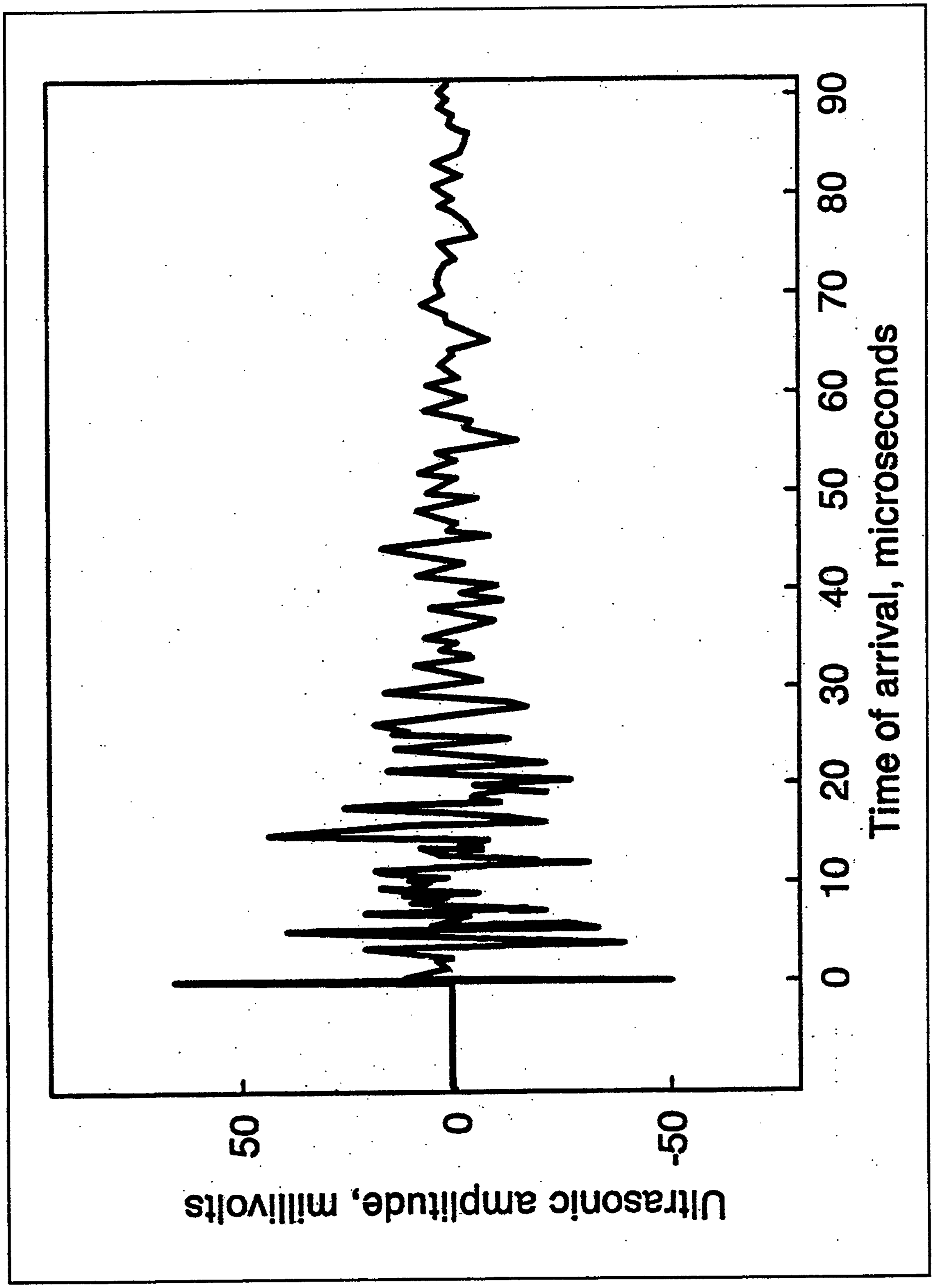


Figure 4. UPE measurement from continuous interfaces

# 3 Engineering of Microcracks

## Procedures for Engineering Microcracks

Three procedures for producing controlled deterioration in the form of microcracks were investigated. One was based on a sulfate-based expansion mechanism, and two were based on an expansive alkali-silica reaction.

*a.* The sulfate-based procedure was based on American Society for Testing and Materials (ASTM) C 452 (1994b), using a high-$C_3A$ cement [RC 756(3)] and varying levels of gypsum, Terra Alba ($CaSO_4 2H_2O$), to cause expansion. Gypsum levels were adjusted to give 1-, 5-, and 15-percent $SO_3$, by mass of cement. Sulfate ions react with hydrated calcium aluminate to form ettringite, a highly expansive reaction product.

*b.* One of the alkali-silica procedures was based on ASTM C 227 (1994a). Mortar bars were made with a high-alkali cement [RC 756(3)] and graded sand (ASTM C 778 1994d) and Pyrex glass as aggregate. Pyrex glass is very reactive with high-alkali cement, resulting in a well-characterized expansion. Six Pyrex/sand combinations were investigated. Three combinations were made by using Pyrex glass passing a No. 100 sieve as 1-, 5-, and 15-percent replacement for the fine aggregate specified in ASTM C 227. The other three combinations were made with Pyrex passing a No. 50 sieve but were retained on a No. 100 sieve.

*c.* The other alkali-silica procedure was also based on ASTM C 227. Mortar bars were made with a high-alkali cement [RC 756(3)] and a mixture of Beltane opal and graded sand (ASTM C 778) as aggregate. Opal constituted 3 percent by mass of the total aggregate. Opal is a somewhat less reactive aggregate than Pyrex, but the expansion mechanism is the same.

The most expansion was obtained from the sulfate-based procedure. Figure 5 shows how the mortar bars expanded against time for the 15-percent gypsum replacement. The rate of expansion was almost constant from 2 days of age up to 22 days.

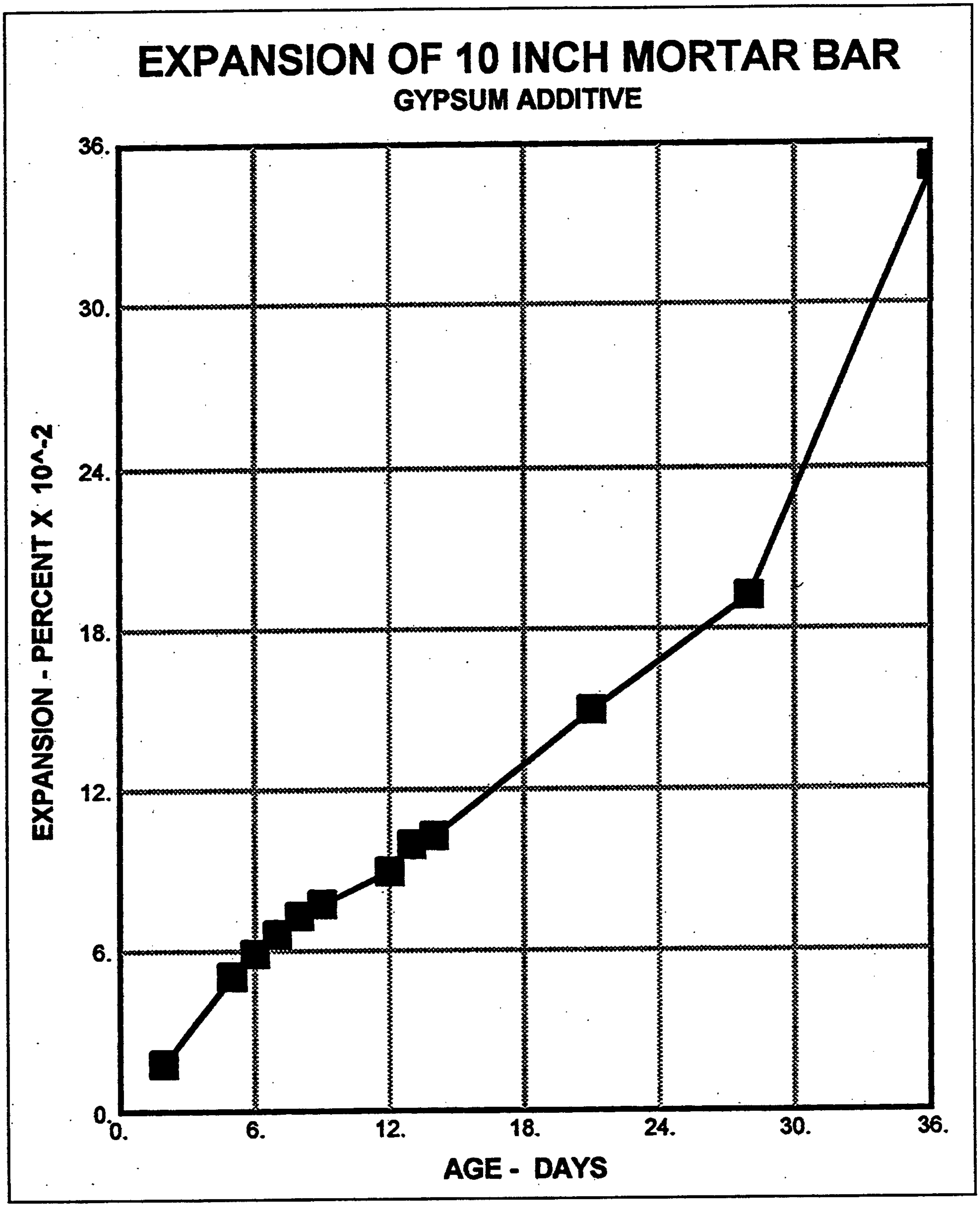


Figure 5. Time-history expansion of mortar bar (254 mm (10 in.))

## Experimentation with Mixture Design of Mortar

The first concrete mixture was based on the sulfate-mediated expansion. Plaster of Paris ($CaSO_4.½H_2O$), supplied under the trade name "Cal-Seal 60," manufactured by the Halliburton Company, was used as the source of sulfate ions because of an inadequate supply of gypsum. The plaster content was 15 percent by mass of cement and caused the $SO_3$ content to be about 8.8 percent, by mass of cement. The concrete, with a water-cement ratio (w/c) of 0.52, experienced problems. The concrete was very dry and experienced a set immediately after it was removed from the mixer before the slump could be measured. There was concern that it might have been a flash (hard) set rather than a false (weak) set. Rather than taking a chance of getting hardened concrete stuck in the concrete mixer, the WES team decided to halt the casting of concrete specimens and make a trial mortar batch to determine if the set could be easily broken by mixing. The coarse aggregate in the concrete was replaced by an equal amount of fine aggregate, by weight, for the test mortar. The w/c of 0.52 was maintained for the mortar, but it was very dry. Although no false set was noticed in the mortar, more Cal-Seal was added to the mixture until a set occurred. The mortar mixer was able to break up the set, and the set did not immediately return when the mixer was shut off. This confirmed that the concrete set was a false set rather than a flash set. It was suspected that a lower-strength design for the concrete might be more likely to expand and develop cracks due to less constraint, so it was decided to increase the flow measurement by increasing the w/c. To get the proper flow measurement on the mortar, raising the w/c from 0.52 to 1.06 was required.

## Design of Concrete Mixture

The cement used in the concrete was RC-756(3), which, as mentioned, had high alkali and high $C_3A$ contents. Plaster, Halliburton's Cal-Seal 60, was the additive used that reacted with the $C_3A$ in the cement to cause expansion. Sodium citrate was added as extra insurance to retard hydration and prevent a false set. The amount of sodium citrate added was equal to 1 percent of the Cal-Seal by weight. One control specimen was cast without the Cal-Seal and sodium citrate. Since, as mentioned, low-strength concrete is more apt to expand and crack than high-strength concrete, the w/c was increased from 0.52 to 0.85. Since the fine aggregate in the mortar has more surface area than the coarse aggregate in concrete, the latter required a lower w/c for the concrete than the 1.06 used for the mortar. It was decided that the cement would be replaced with the same 15 percent of Cal-Seal as determined by the mortar bar testing. One control specimen was cast without Cal-Seal, and the other five specimens contained the same amount of Cal-Seal. Both the fine and coarse aggregate were of limestone. The coarse aggregate had a maximum diameter of 19 mm (3/4 in.).

## Accelerating the Reaction

It was desired to manufacture at least six specimens that had varying degrees of deterioration from chemically induced cracking. Rather than attempt to vary the percentage of Cal-Seal to obtain various levels of defective concrete, a different method was tried. Since the reaction is dependent on the presence of moisture and temperature, it was decided to immerse the major part of each specimen in water at 38 °C (100 °F). A rule of thumb states that the rate of reaction doubles for every 5.6-C° (10-F°) increase in temperature. When the proper level of deterioration had been obtained, then the specimens were to be removed from the high temperature and moisture in hopes of terminating the expansive reaction at that level of deterioration.

## Placement of Concrete

Six forms made of marine plywood were used to cast 2- by 2- by 0.5-ft (0.16- by 0.61- by 0.15-m) specimens. After mixing, it was determined that the slump of the control specimen measured 89 mm (3-1/2 in.). The slump measured 152 mm (6 in.) in the first batch of test concrete, and the slump was not measured in the next three batches. The slump was higher in the evaluation specimens, probably due to the retardation from the sodium citrate. The concrete was placed in the forms, and metal supports were inserted into the fresh concrete as a base for bonding metal tabs for length-change measurements with the Whittemore gauge (later it was found that the moisture from the water bath kept causing the bond to fail on the tabs and this procedure was abandoned). The concrete was poker-vibrated, and the top surface of the concrete was screeded level with the forms. The concrete was then covered with wet burlap and covered with a sheet of vaporproof plastic for a couple of days before stripping the forms.

## Curing of Specimens in Hot Bath

The forms were stripped on the second day after casting, and the specimens were moved to a water bath in the temperature-controlled room. The water bath temperature was maintained at 38°C (100 °F). At that time, the specimens were supported on one of the 0.61- by 0.15-m (2- by 0.5-ft) ends, and the water was brought to a height of 76 mm (3 in.) above the base of the specimens. After 17 days, the specimens had not experienced any expansion, and the water level was brought up 76 mm (3 in.) more. When no expansion was observed for 4 days, the water level was brought up to the full height of the tank. The specimens were then submerged to a depth of 406 mm (16 in.). Eight inches (two-hundred-three millimetres) were left above the water level, but the specimens were still covered with wet burlap and a vaporproof plastic sheet. The water level was maintained by occasionally adding water to the tank as it evaporated.

## Deterioration-Measurement Standards Created

A plot of the UPVs through the 0.61-m- (2-ft-) wide specimens is shown in Figure 6. It was decided to increase the interval between measurements, since there was no noticeable change in UPV until after about 23 days of curing in the water bath (UPV measurements were made every weekday from the day the specimens went into the water bath) and the concrete was obviously not duplicating the action of the mortar bars (Figure 5). Although cracking was still not detectable visually after about 28 days, the UPVs had begun to decrease. However, the investigators failed to note the significance of the change and almost forgot to continue their measurements until the 48th day. At that time, it was finally noticed that one of the specimens had developed numerous cracks. It was immediately removed from the water and heat and stored at normal room temperature and humidity. The V-meter was used to make the UPV measurements, and the frequency of operation of the transducers were 54 kHz. It was interesting to note that the reaction had different rates for each of the five specimens, although they were supposed to be identical. All of the specimens were removed from the water bath on the ages of 48, 49, and 50 days. UPV measurements were continued after the specimens were taken to a dry room with temperature about 40 °C (72 °F). The direction of the UPVs turned around and increased for awhile until they reached a constant value after about 1 week. The UPVs varied from about 1,737 m/sec (5,700 ft/sec) for Specimen No. 6, the specimen having the worse deterioration, to about 4,877 m/sec (16,000 ft/sec) for the control specimen. A time-history of the UPV for Specimen No. 6 can be seen in Figure 7. Note that the velocity of Specimen No. 6 dropped to about 1,280 m/sec (4,200 ft/sec) (Figure 7) while in the bath but increased to 1,737 m/sec (5,700 ft/sec) (Figure 6) after being removed from the bath for 1 week.

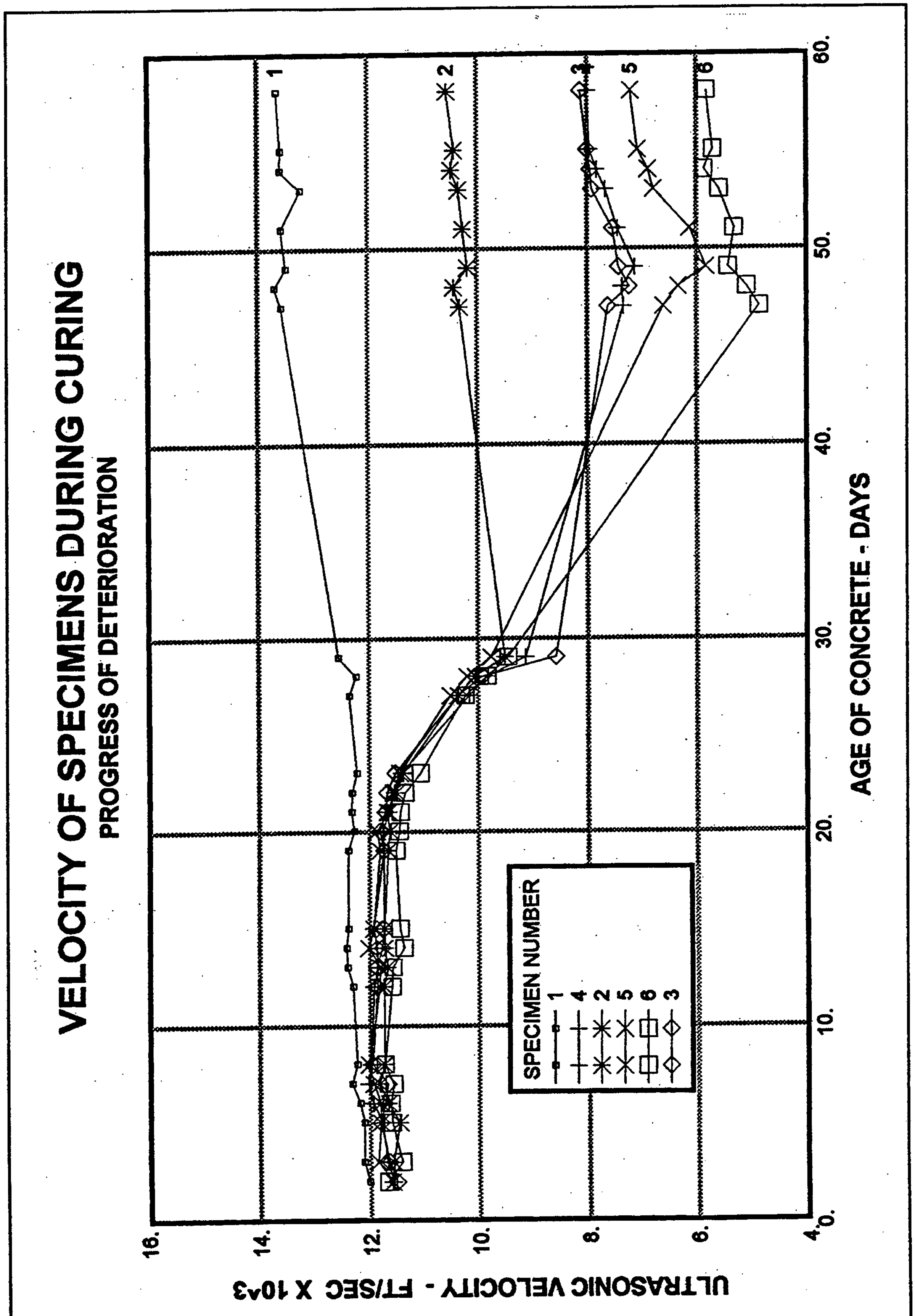


Figure 6. Time-history of UPVs of all six specimens during curing (304.8 m/sec (1,000 ft/sec))

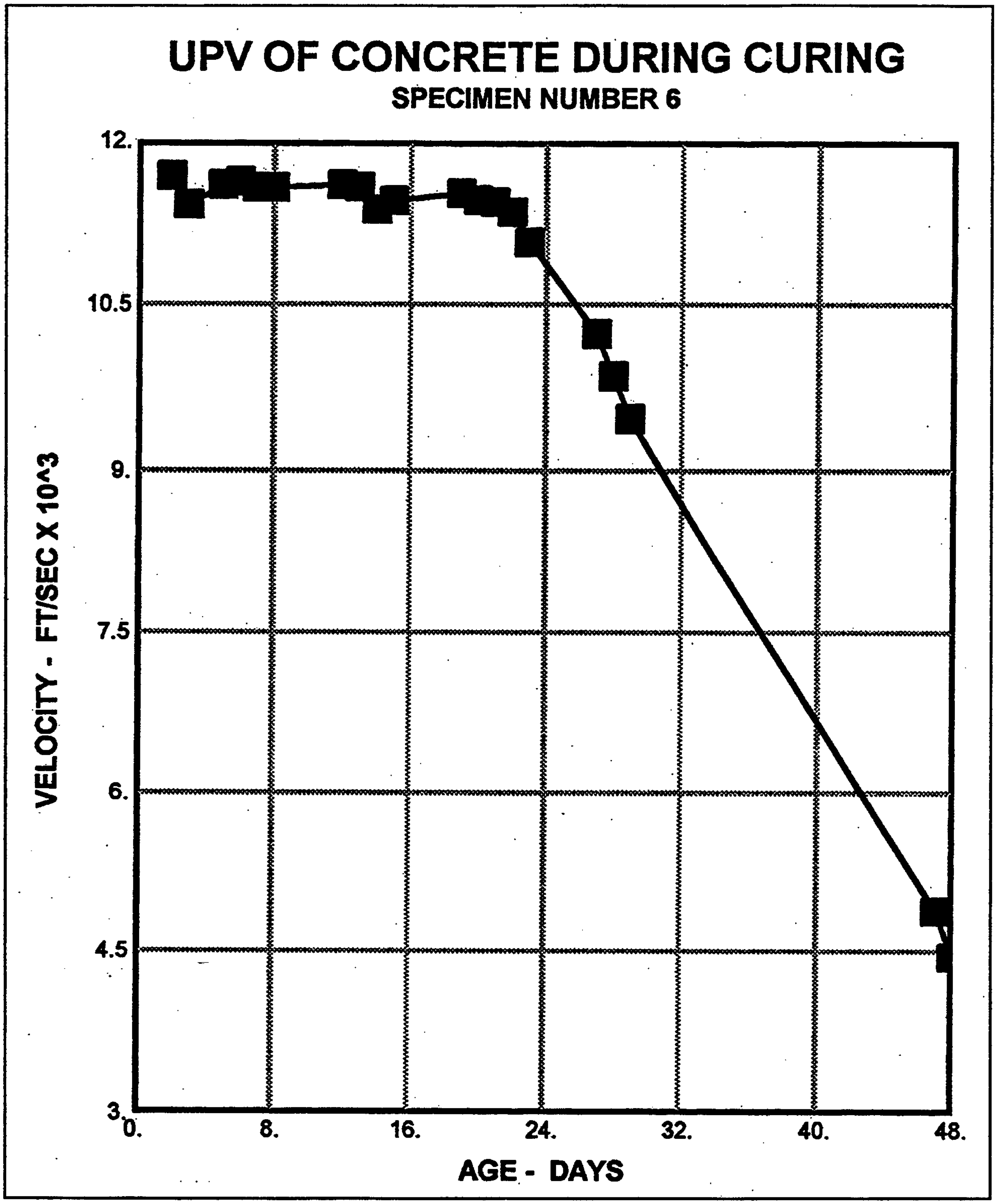


Figure 7. Time-history of UPVs of Specimen No. 6 (304.8 m/sec (1,000 ft/sec))

# 4 Ultrasonic Measurements for ANN

## Rating the Degree of Microcracking

It may be intuitive that the UPE signals contain information about the degree of microcracks in a concrete specimen. However, without having a standard method of classifying the degree of microcracking in each deterioration standard, it is not possible for the ANN to develop an association between the UPE signals and the degree of cracks in each specimen. A method is needed to classify the degree of cracks that can be specified in a number of ways. One could count the number of cracks on a given surface and use that number as an index to classify the amount of cracks throughout the specimen; or one could measure the amplitude of attenuation of an ultrasonic pulse through the concrete. On the other hand, one could measure the UPV through the thickness and determine an index.

The V-meter measures the UPV according to ASTM C 597, "Standard Test Method for Ultrasonic Pulse Velocity Through Concrete" (1994c). This was chosen to be the method for rating the degree of microcracks, because the UPV was very sensitive to the deterioration. (Remember that UPV measurements require access to opposite sides of the specimen and can easily be performed in the laboratory; whereas in the field, many structures such as bridges, pavements, etc. have only one surface that is readily accessible.) These UPVs would provide the target values that the ANN would aim for in the training phase.

It was decided not to core the specimens and develop a calibration curve relating the UPVs of the cores with the compressive strength of the cores. The investigators wanted to keep the standards for future ultrasonic and radar testing. Although the compressive strength is considered by some people to be an absolute criterion for measuring the quality of a concrete element, the researchers opted for the UPV evaluation, a comparative evaluation, as the indicator of deterioration, so that they would not have to sacrifice the specimens. Also, it is known that UPVs can always be calibrated against compressive strength with the proper calibration curves should the researchers choose to do so at a later date.

## Collection of UPE Training Data for ANN

Figures 8 and 9 show all of the microcracked specimens and a close-up of one of the more heavily cracked specimens, respectively. The cracks were labeled with a black marker to visually emphasize the deterioration. Although only a few cracks were highlighted for the photographs, there were many more present on the surface.

The measurement configuration is shown in Figure 10. The WES researchers chose measurement locations near the center on each specimen to prevent interfering, extraneous echoes from the boundary. (Rayleigh waves travel on the surface and can be received from the boundaries before the longitudinal echoes can be received from the backwall, if the measurement is made too close to the edge of the specimen). The total number of UPE measurements is equal to four measurements per location times nine locations per specimen times six specimens, or 216 total measurements. The WES researchers made the four UPE measurements at each grid intersection by rotating the transducers 90 deg each time to make the transducer coupling variable.

The researchers measured the level of deterioration in nine locations by making UPV measurements through the 152-mm (6-in.) thickness of each of the specimens with the V-meter. The ANN would use the UPE measurements as the input and the UPV measurements as the target data. In other words, these four UPE signals would see one level of deterioration as determined by the V-meter reading.

## Broad, Uniform Distribution of Deterioration Created

Although there were six specimens whose mixture design was meant to be identical (one control did not contain sulfate), the amount of deterioration was variable in the specimens with age. The deterioration occurred at different rates for each of the specimens, permitting the WES investigators to obtain a fairly uniform distribution of velocities and hence deterioration. Also, there was variability of the UPV throughout a given specimen. The target velocities were obtained through the 152-mm (6-in.) thickness (remember the curing velocities were obtained through the 0.61-m (2-ft) dimension that was above water). The distribution of the target UPVs is shown in Figure 11. Actually, a very uniform distribution of UPVs ranging from about 1,737 m/sec (5,700 ft/sec) in Specimen No. 6 to about 4,877 m/sec (16,000 ft/sec) in the control specimen (Specimen No. 1) was obtained.

Figure 8. All six microcracked specimens

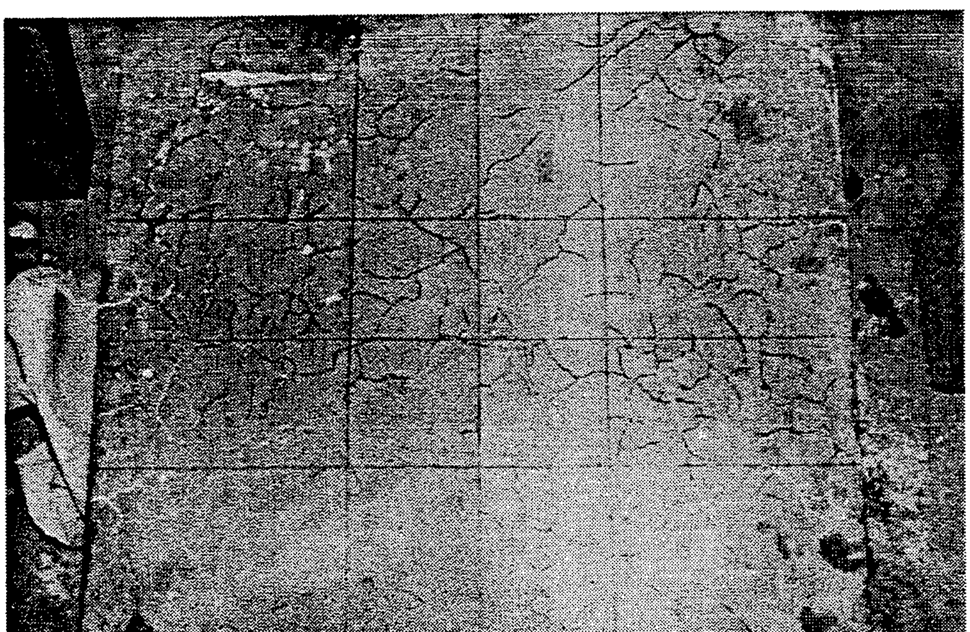

Figure 9. Close-up of one microcracked specimen

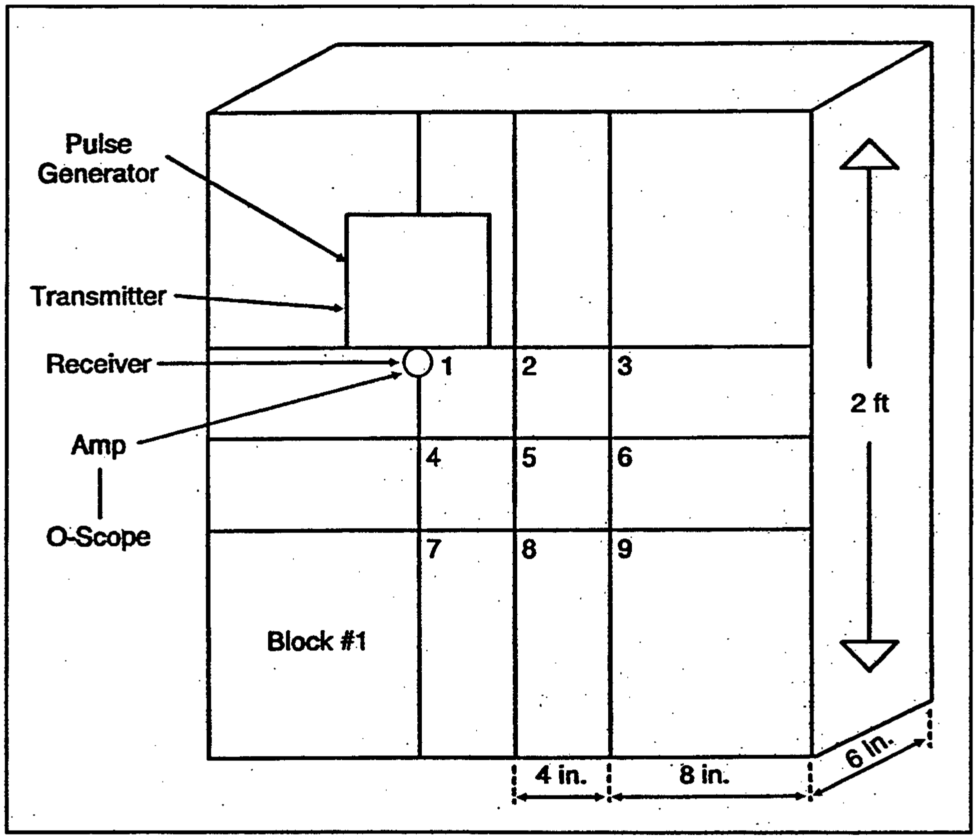


Figure 10. Measurement configuration. (To convert inches to millimetres, multiply by 25.4; to convert feet to metres, multiply by 0.3048.)

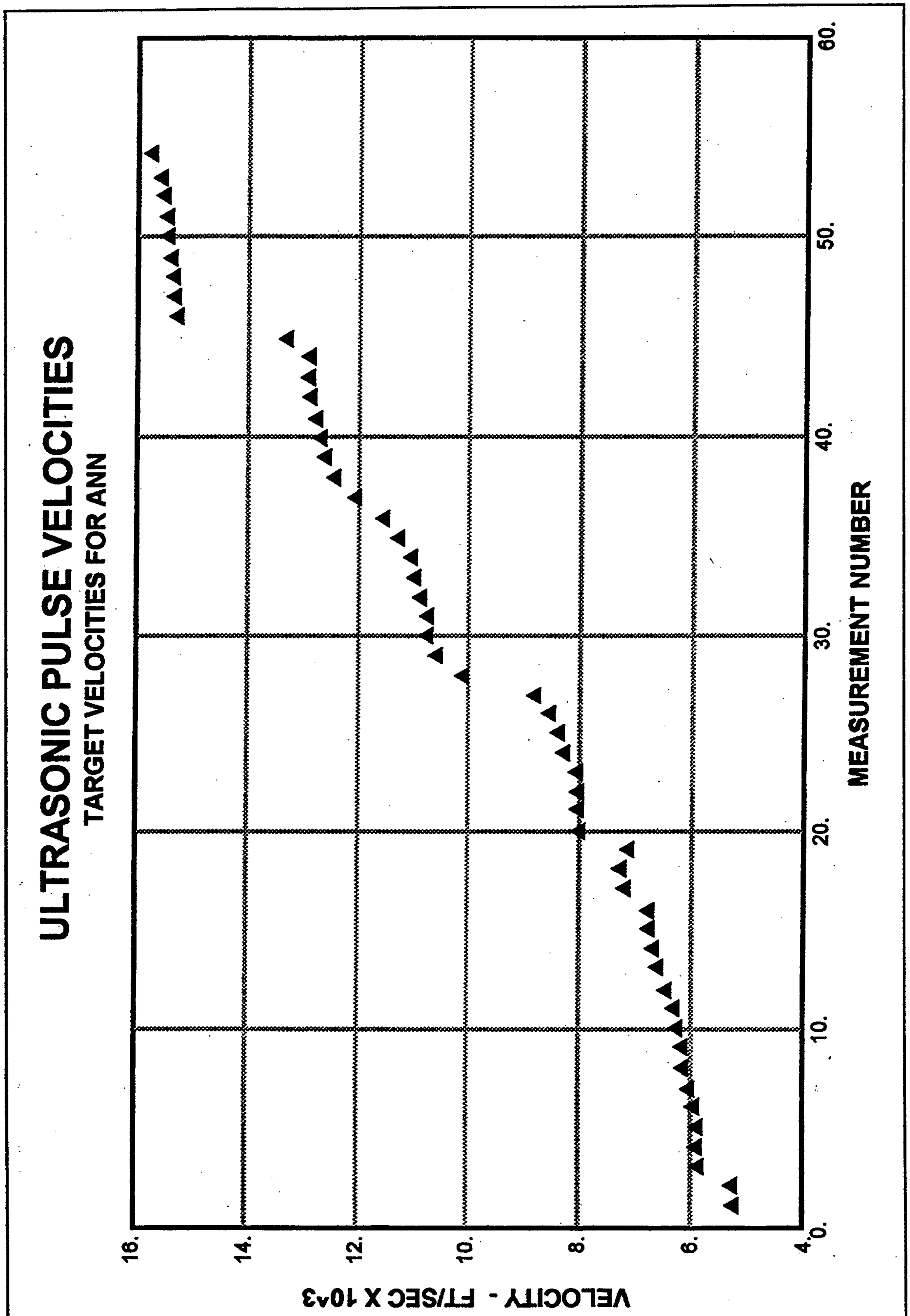


Figure 11. Target UPVs of deterioration standards for ANN (0.3048 m (1 ft))

# 5 Application of ANNs to UPE Data

## Description of ANN Neuron and Architecture

ANNs are designed to mimic the operation of the human brain; hence, they are referred to as a branch of artificial intelligence. The brain has a significant capability to perform pattern recognition, and the ANN system can emulate the functions performed by the biological neurons and are ideal for real-time results. A diagram of an artificial neuron is shown in Figure 12. The input lines model the dendrites (input nerve fibers) of the brain. They collect the activity being received, similar to the brain, and pass it on to the following artificial neuron in the network. The output lines model the axons (output nerve fibers) of the brain and receive the information from the artificial neuron and pass the processed information to the next artificial neuron in the network. The weights on the connection lines and the biases on the transfer function model the synapses of the brain which determine the importance or lack of importance of a particular activity arriving at that point (Hinton 1992).

The following illustration points out how the weights and biases are adjusted in the ANN. Human beings learn by repeatedly observing the outcomes of their responses to external stimuli. Consider the process of learning how to shoot a basketball properly. There are many input variables (independent variables) that determine the success of the shot, and in the beginning of the learning process, it is difficult to know which variables are important and which are not. There is only one output variable (dependent variable), and that variable is the proximity of the basketball to the net once a shot is made. If the basketball hits the net the majority of the time that the basketball is thrown, then the person is properly trained and all the synapses (weights) in the brain are properly adjusted to indicate the importance of the various input variables. Variables such as how to place one's feet, how to bend or not bend one's body, the direction that a person's body faces, the correct placement of one's hand(s) on the ball, the position of the arms, etc., might be important variables. After an individual throws the basketball a few thousand times and continually notes the error between the actual outcome (where the balls lands) and the target solution (a basket), the feedback to the brain will result in an automatic adjusting of the weights for each variable until the shooter begins to get better at hitting the basket. Maybe the

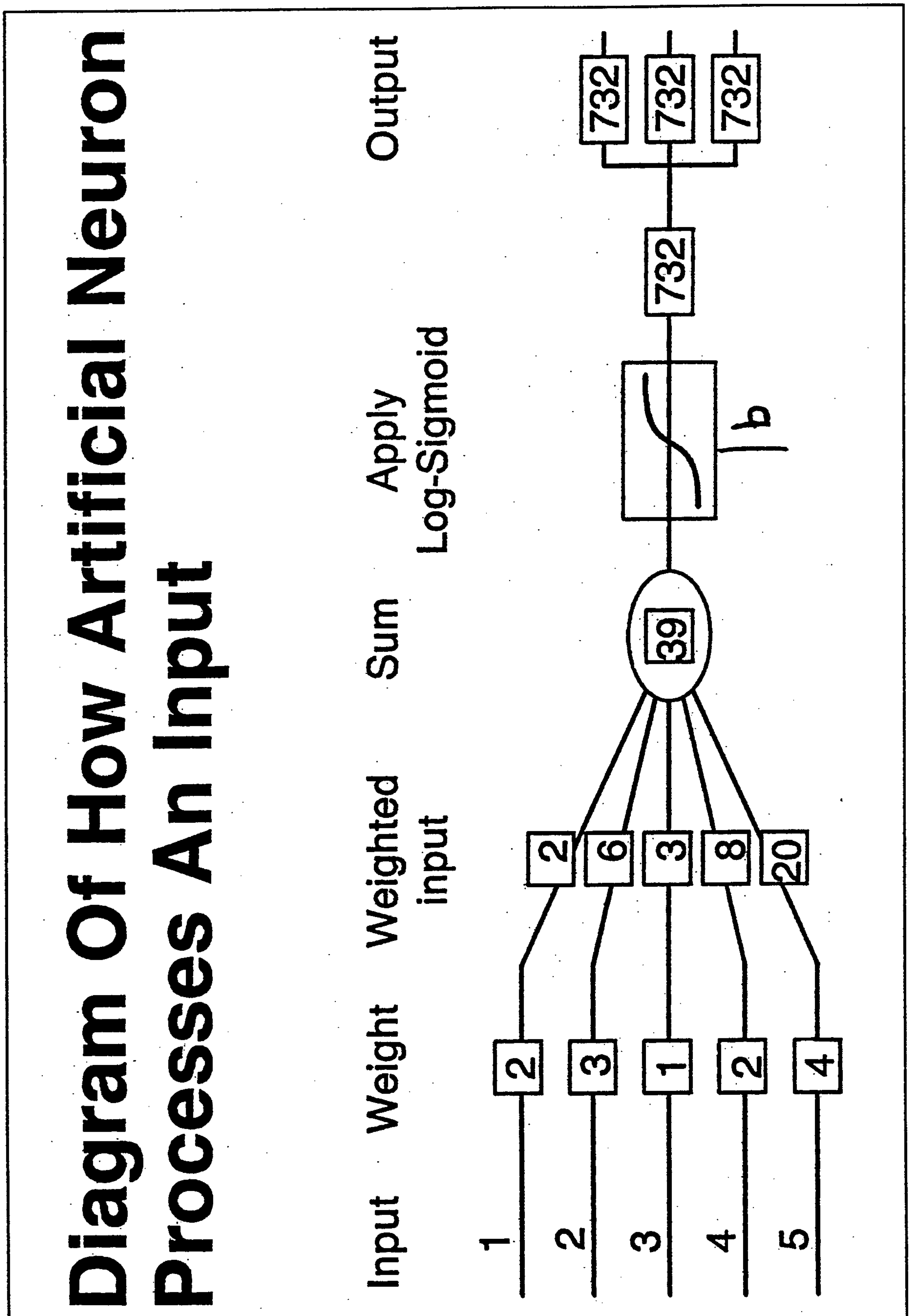


Figure 12. Diagram of artificial neuron

individual will find that the type of shoes worn or what was eaten for lunch is not too important for hitting the basket; so those weights will take on a low or zero value for their importance. In this same manner, the ANN learns how to get closer and closer to the target values of the problem.

There are many classes of ANNs: perceptions, linear, back propagation, radial basis networks, etc. The architecture can differ within a class. The type of problem being solved determines the class chosen. The architecture of a network consists of a description of the number of layers a network has, the number of neurons in each layer, the type of transfer function in each layer, the way the layers are connected to each other, and the number of network inputs. Both the neuron model and the architecture of the neural network determine how a network transforms its input into an output. ANNs have the potential to reduce the calculation time required as many inputs can be received in parallel, weighed, and analyzed simultaneously. The data in this investigation were not trained or tested in parallel, but they could be implemented in parallel for the field unit should the calculation time need to be reduced for faster real-time results.

# Design Considerations for Creating Model

## Transfer functions

The software used in this investigation was the Neural Network Toolbox by MATLAB™ (Demuth and Beale 1992). This package has a number of features that permit an improvement in the procedure to develop optimal ANN models for a particular application. The package contains a number of transfer functions, but three of the most popular are the hard limit or threshold output (values of 0 or 1), linear output (any value), or nonlinear output (any value between -1 and 1). The problem in this investigation required the use of the nonlinear transfer function. It is not possible to get the correct output for a problem without choosing the proper transfer function. All of the transfer functions in MATLAB™ have the option of including a bias for the transfer functions. The bias can be a constant, or it can take on a value as it learns. This particular investigation used the bias that learns. The net input of the transfer function is the sum of the weighted inputs wxp and the bias b, where w represents the value of the weight for that neuron and p represents the value of the input arriving on that connection line. The sum of all weights (w) times the input value (p) plus b is the argument of the transfer function.

## Determination of architecture

The architecture of the network of artificial neurons that was ultimately used in this investigation is shown in Figure 13. The multiple-layer feed-forward model was the appropriate model for this investigation. (Feed-forward means that the information flows in only one direction through the network.) This

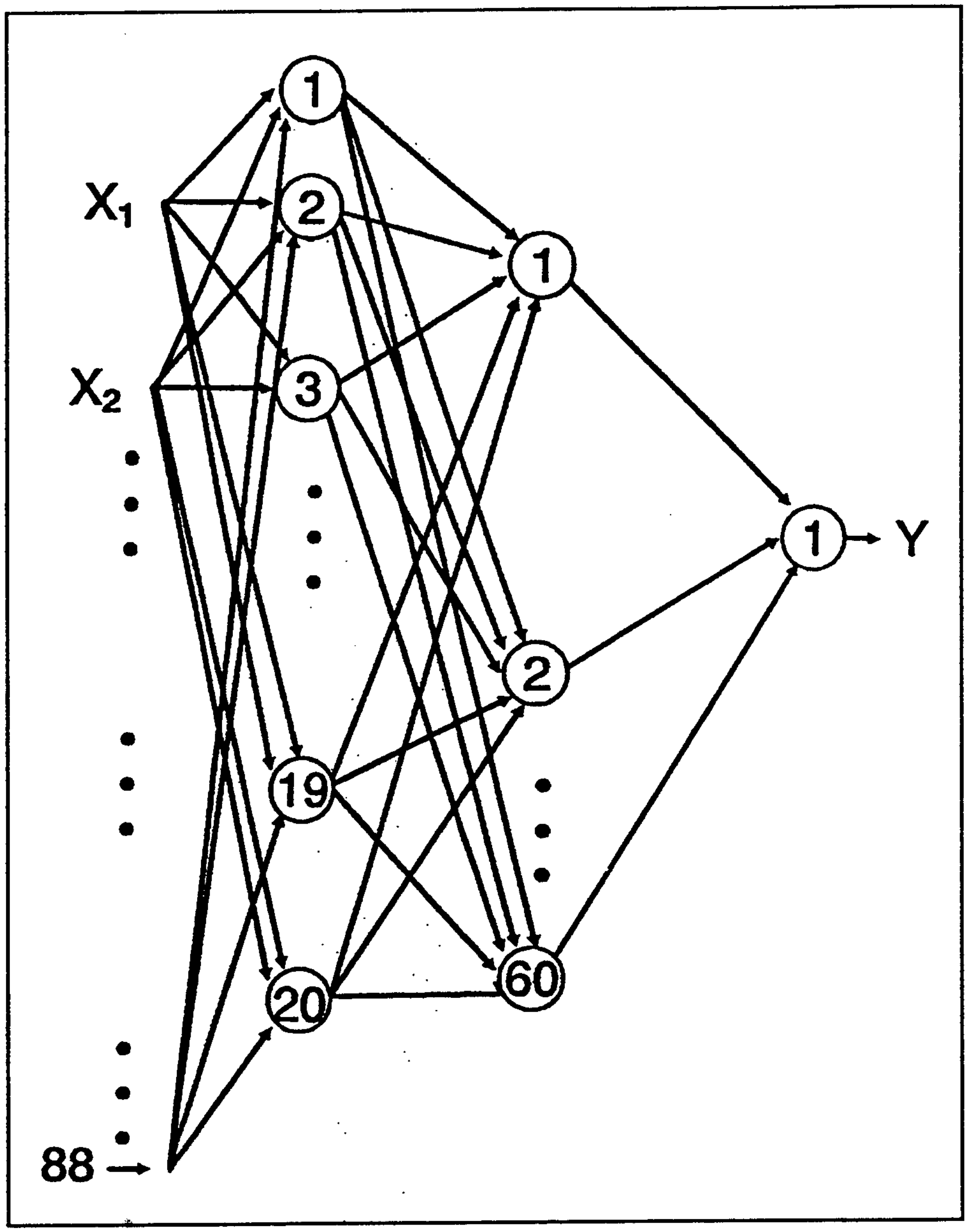


Figure 13. Ardchitecture of artificial neural network

configuration requires the back propagation (BP) learning rule for training the network. The architecture of a BP network is not completely determined prior to training by the problem to be solved. It is an empirical process that takes some time to develop. The number of inputs to the network is related to the number of neurons in the first layer, and the number of neurons in the output layer is constrained by the number of outputs required by the problem (in this case, one). However, the number of layers between the first and the output layer and the number of neurons in those intermediate or hidden layers are up to the designer.

## Importance of hidden layer

It requires a trial-and-error process of checking the error in the training and evaluating to optimize the hidden layers. (They are called hidden layers because they are not in direct communication with the input and the output data.) In fact, it has been determined that no significant improvement is obtained by increasing the number of hidden layers from one to two. Also, the training time increases exponentially with more layers (Er et al. 1995). Optimizing the number of neurons in the hidden layer is of critical importance. The more nodes the hidden layer has, the more complex the mapping an ANN can perform. (Mapping is the mathematical process within the ANN that permits it to correctly convert the input into output data.) However, too many nodes in the layer can increase training time and cause memorization or overfitting of the data. The mapping can be overly specific to the training set and unable to generalize for other similar type data (Kirk and Lewcock 1995). Insufficient learning takes place if there are not enough nodes (neurons) in this layer. This is also referred to as underfitting of the data. MATLAB™ has a graphical representation that permits one to observe the error during training.

## BP learning rule

The learning rule referred to as the BP algorithm follows the mathematical method of steepest gradient descent to minimize the network error from the error equation. The difference between the network output value and the target value is calculated and then squared for each epoch (an epoch is one iteration of all the data) for each of the 186 signals. Then the squared terms are summed from all the outputs to determine the total error from all training signals. This error (not the data) is then *propagated backwards* through the network, and the weights and biases are changed in proportion to the magnitude of the error. After several thousand epochs, the network is trained. The error equation can be visualized as an error surface where there are local and global minima. The smallest error results when a global minimum is found. The process can be illustrated by a mountain range (Demuth and Beale 1992). In that mountain range are many valleys, and only one of them has the lowest elevation. That is the global minimum that is being sought in the training. As mentioned, the BP learning rule follows the mathematical technique of steepest gradient descent. Imagine a marble rolling down a surface; the route it would take to get to the lowest elevation, the quickest, would be that of the steepest gradient descent. There are a couple of disadvantages of the BP learning rule: (a) a slow learning speed and (b) the risk that a local minima may trap the network before reaching the desired global minima. The more neurons in an intermediate layer, the more freedom a network has (i.e. more variables to optimize) to find a global solution or a low error for a local solution. Although more neurons increase the training time, they also increase the chance that a local minimum will yield a low error, assuming one is unable to obtain the global minima.

For the first iteration of the input data, the weights and biases are set randomly. However, it may be that the first try will yield a poor solution. It may

not be possible to find the global minimum, and the error of the local minimum that is found may not be satisfactory. A trial and error process of reinitializing the weights and biases may be necessary. The initialization process can be thought of as the starting position that is given to the marble somewhere on the mountain. Some starting positions on the mountain for the marble are more advantageous, and it may obtain a lower valley at a faster rate than some other position.

### Learning rate and momentum

Adding a momentum term to the BP algorithm decreases the probability that the network will get stuck in a shallow minimum on the error surface and helps decrease training times. The momentum term causes the weight to adjust steadily in the same average direction. Another important parameter in the training is the learning rate. This network parameter controls the rate of the weight adjustment. Too large a value for the learning rate results in unstable learning. The network can jump over valleys in the error surface that may give a suitable solution. Too small a value results in incredibly long training times. An adaptive learning rate decreases training time by keeping the learning rate reasonably high while ensuring stability.

## Data Preparation, Training, and Performance

### Development of measurement criteria for microcracks

Some measurement criteria were developed for microcracks rather than training the ANN system on the raw input data. It was found that the higher frequencies of the reflected ultrasonic pulse are attenuated more from specimens having greater deterioration than from those specimens that are of higher quality. Also, the cumulative reflected energy of the UPE signals is less for the more deteriorated specimens than from the specimens that are sound. The dissipation of energy is probably greater because many of the smaller wavelengths (higher frequencies) from the transmitted pulse that correspond to the dimensions of the cracks encounter more obstacles in the specimens having greater deterioration and create scattering and destructive interference.

### Preprocessing of signals to emphasize important information

Although it is not necessary to determine the relationship between signal features (independent variables) and deterioration (dependent variable) for training the ANN, it saves training time and makes the system more sensitive when the signals are preprocessed to emphasize the critical features, remove unrelated information, and reduce the amount of data. Figure 14 shows how typical raw signals from microcracked specimens as seen in Figure 4 have been conditioned to make the input data more sensitive for the ANN. First, the time-domain signal was converted to a frequency-domain signal by taking the Fast

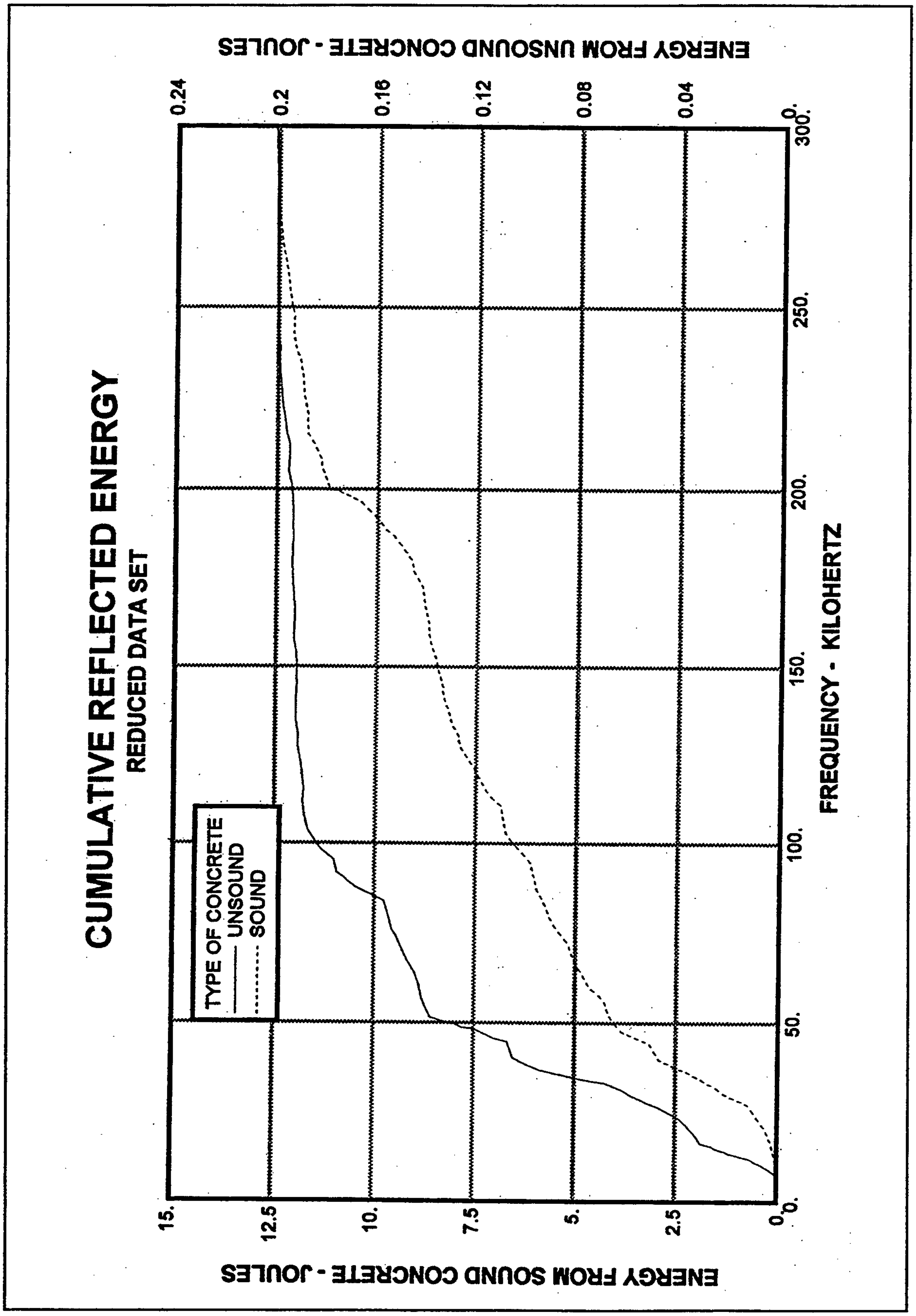


Figure 14. Processed signals for sound and unsound concrete

Fourier Transform (FFT) and obtaining the power spectral density (PSD). Then, the PSD or energy curve was integrated with respect to frequency to yield the cumulative energy curve seen in Figure 14. This particular procedure for signal manipulation is known as Parseval's theorem. It was noted that of the 2,048 points in each integrated curve, only the first 352 points carried the bulk of the information. That is, there was almost no energy above 352 kHz. All points were trimmed from the data above the 352 points. Then the curve containing the 352 points was decimated by removing 3 points for every 4 to reduce the information to 88 points. Since the curve was smooth, no significant information was lost in reconstructing the shape of the curve with fewer points.

## Concrete acts as low-pass mechanical filter

The curve on the bottom of the graph (Figure 14) was obtained from measurements on sound concrete and shows that the accumulated reflected energy (12.5 joules) is high for the sound concrete. The curve on the top shows that the accumulated reflected energy (0.2 joules) is lower for one of the blocks possessing the unsound concrete. The cumulative energy from the unsound concrete is only about 1/60 of the cumulative energy from the sound concrete. Also, it was noted that the cumulative energy from the sound concrete is made up of both low and high frequencies. The reflected energy from the unsound concrete is made up of only lower frequencies (<100 kHz), since the higher frequencies (>100 kHz) have been filtered by the deteriorated concrete. The concrete acts as a mechanical low-pass filter on the energy components of the ultrasonic pulse.

## Training procedure for ANN

The ANN is trained by supervised learning. The process of supervised learning is accomplished by presenting the network with a set of input and output values. Then, the connection weights are altered by a process called learning. Each of the 186 signals used for training the network contained 88 points. Five UPE measurements were reserved from each concrete block for a total of 30 signals for testing the performance (validation phase) of the trained network. The connection weights and biases were given random values for the first iteration. It took over 50,000 epochs and 15 hr to train the model. The ANN looks at its own error for each signal by subtracting the network-estimated velocity (network output) from the measured velocity (target values), squaring the difference, summing all the squared differences for each signal, calculating the mean of those errors, and using the magnitude of the error to proportionally readjust and recalculate all the weighing factors until the error function is reduced to a minimum.

## Performance of ANN on training data

The graph in Figure 15 shows the difference between the output UPV that the ANN estimated and the target UPV. The least-squares fit gave a correlation

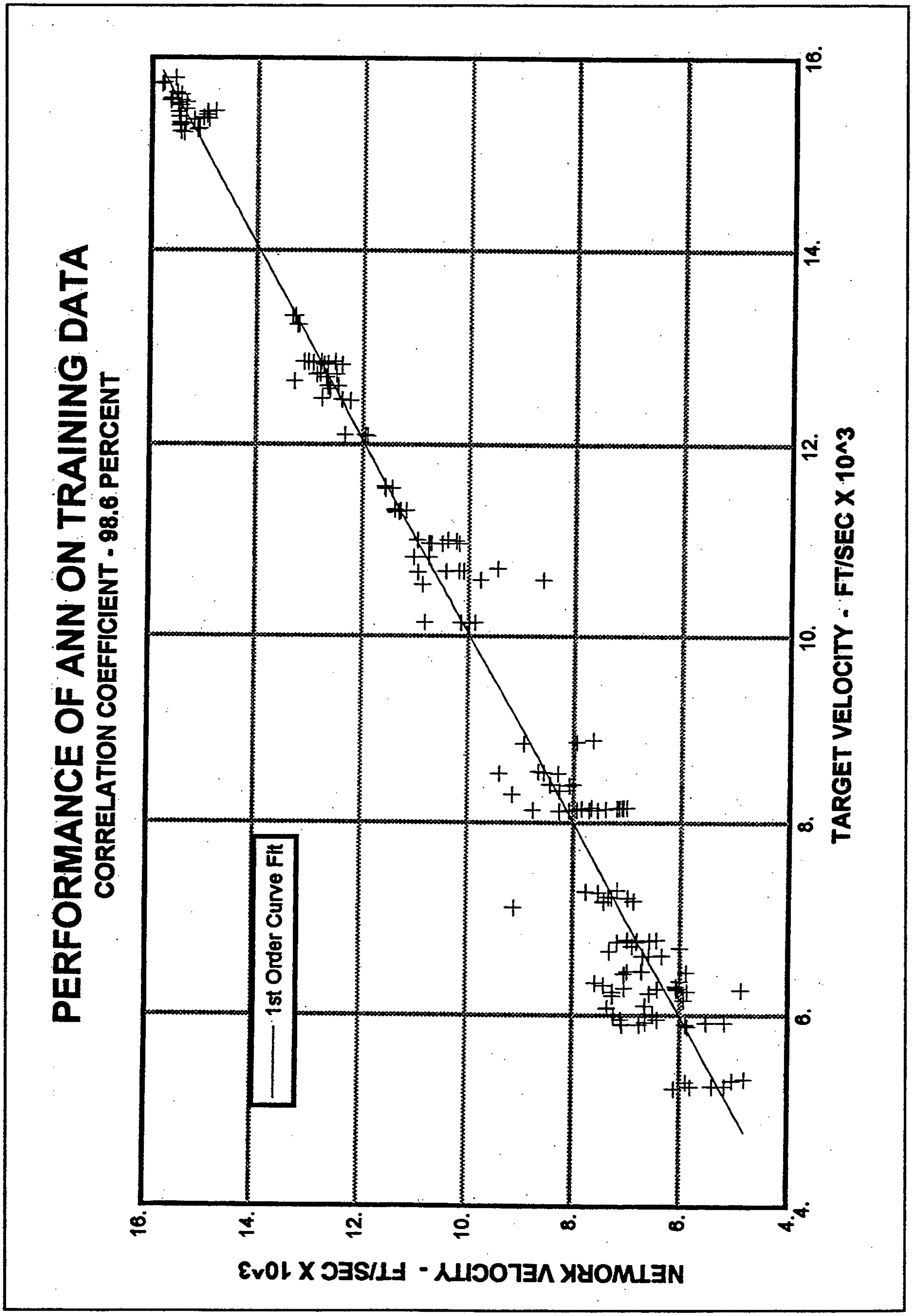


Figure 15. Performance of ANN on training data (0.3048 m (1 ft))

coefficient of 98.6 percent. The greatest error in the interpretation lies in the range from 2,438 to 3,353 m/sec (8,000 to 11,000 ft/sec). It is important that the network be able to generalize beyond the training examples instead of simply memorizing them. In the literature, memorizing is also referred to as overfitting and overlearning of the data. Also, the ANN should never be trained with the data used to test the model (Meier and Rix 1995).

### Performance of ANN on test data

Figure 16 shows the performance of the ANN system to estimate the target UPV on specimens not used in the training. The x-axis is the target velocity, and the y-axis is the output velocity. A least-squares fit of the data yielded an 84.8-percent correlation coefficient. The performance of the ANN was better in predicting sound concrete. Although the fit was satisfactory, it is possible that the fit can be improved. Since the fit on the training data was high (correlation coefficient 98.6 percent), the network might have overlearned (overfitted, memorized, etc.) the data and was unable to generalize on the test data properly. Remember that the test data came from the same concrete standards and should have been representative of the training data.

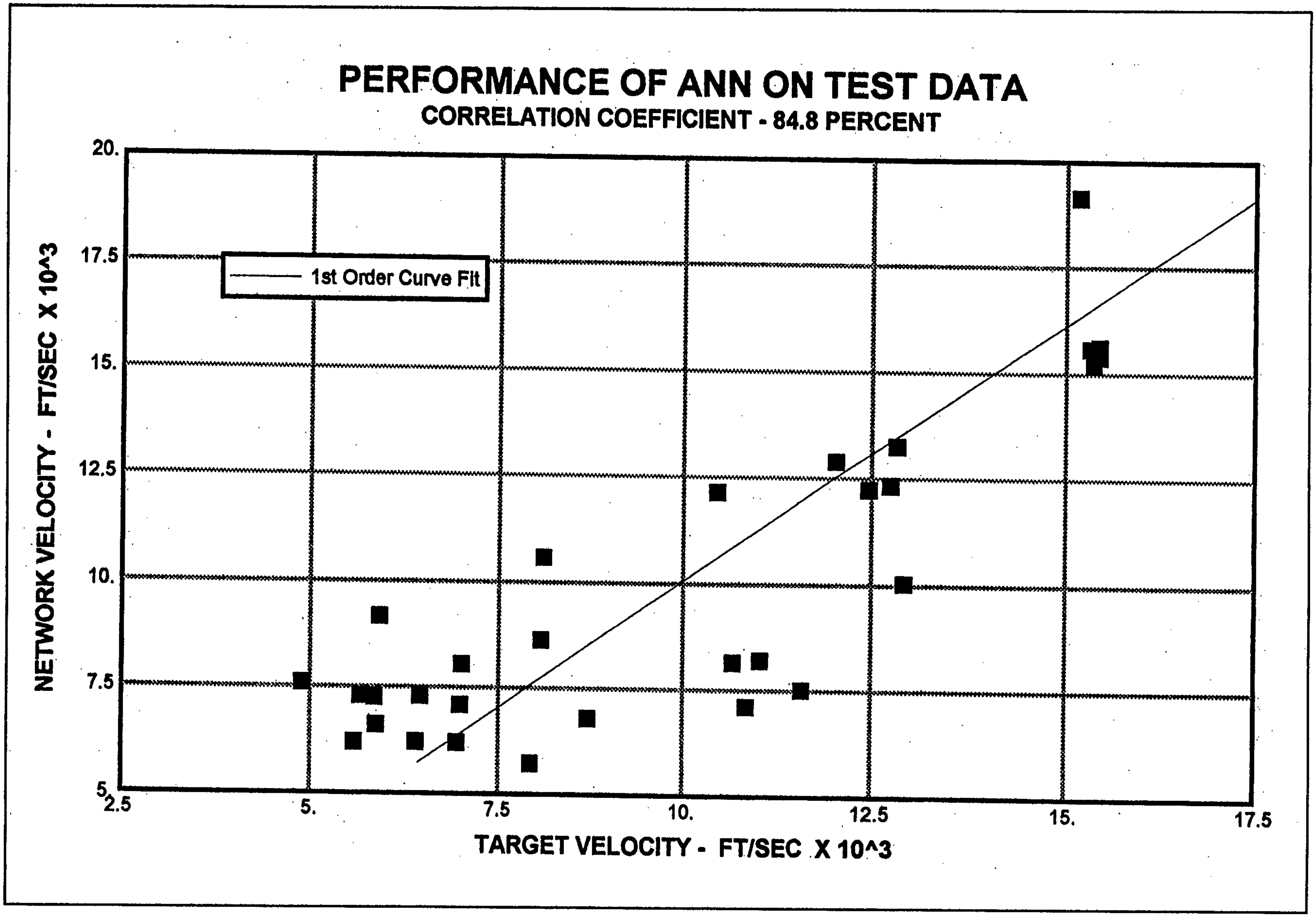


Figure 16. Performance of ANN on evaluation data (0.3048 m (1 ft))

# 6 Conclusions and Recommendations

## Conclusions

This is a first attempt in civil engineering to create concrete deterioration standards containing uniform microcracks of differing degrees. This investigation was initiated to determine if it was feasible to use the ANN to automate the interpretation of UPE signals made from concrete possessing deterioration of the continuous-interface type. The result of this investigation indicates that the ANN can be used to automate the interpretation of UPE signals and does it efficiently. The system was able to rank all six concrete deterioration standards in the correct order of deterioration.

Later tests in the laboratory on a poor concrete indicated that the V-meter does not measure the correct UPV for weak signals. The display of the TOA of the pulse from the V-meter is apparently triggered by a threshold circuit. If the ultrasonic pulse arriving at the receiving transducer has been seriously attenuated, the system may trigger on the fifth cycle, the ninth cycle, or the number of the cycle that has enough amplitude to trigger the display rather than the desired first cycle. The result of this phenomenon is that the V-meter measurement obtains a number that may be more closely related to the attenuation of the concrete rather than the UPV of the concrete. As noted earlier in the text, the quantity measured for the target velocity is not important as long as that quantity correlates with the degree of deterioration. However, for those who may attempt to reproduce this work, it may be advantageous to keep the consideration above in mind.

It should be noted that the ANN is not sufficient alone to provide the complete job of automation for defects of the continuous-interface type. A number of conventional or standard types of signal processing techniques, such as FFT, mathematical integration, PSD, etc., would be required to complete the job of automatic interpretation. Other types of signal processing techniques can be used to clean the data of noise, enhance certain desired features, and eliminate other unwanted features.

The use of the ANN in automated systems has the potential to reduce dependency on highly skilled personnel, make use of less-experienced personnel,

and permit higher consistency in the decision-making process for evaluating the condition of concrete. Development of a UPE field unit with an on-line computer for making real-time data acquisition and interpretation is now occurring under the U.S. Army Corps of Engineer's Construction Productivity Advancement Research Program. This system should permit an improved detection of delaminations in bridge decks.

## Recommendations

Only one concrete mixture design was studied. Now that it has been shown that the ANN performs well within the limits of the study, future work should consider other variables, especially the various types and sizes of coarse aggregates. The results of this investigation should allow the technology to have widespread use when commercialized, should the UPE system gain popularity. As the authors were very early on the learning curve in 1992, the ANN model developed may not be an optimum model. Although it may perform well, it is believed that the training time, complexity, and the performance of the network on test data can be improved. More is now known about the importance of optimizing the number of neurons in the hidden layer, processing the input data in such a way that the amount of data fed to the network can be reduced further, and the introduction of complex neurons into the field of ANN. Recently, the ANN has been developed to take a complex input rather than a real input as was done in this investigation (Masters 1994). UPE signals have the property of the signals being composed of magnitude and phase when transformed to the frequency domain and, hence, are ideally suited for complex neurons.

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**13. ABSTRACT** *(Maximum 200 words)*

Concrete deterioration standards containing various levels of microcracks were engineered by adding calcium sulfate to the concrete mixture and curing under moisture at 38 °C (100 °F). The level of the mircocracks was classified according to the speed of the ultrasonic pulse velocity (UPV) through the specimens using the American Society for Testing and Material (ASTM) C 597 (ASTM 1994c) test method and was found to vary uniformly from 1,737 to 4,877 m/sec (5,700 to 16,000 ft/sec). After receiving some preprocessing, 186 ultrasonic pulse echo (UPE) signals were used as input training examples for the artificial neural network (ANN) system. Target values for the ANN were the measured UPVs as determined form the ASTM C 597 test method. The correlation coefficient from a least-squares fit was 98.6 percent. After training, the ANN was performance tested with 30 UPE signals that the model had not seen in training. A least-squares fit demonstrated that the output velocities from the ANN correlated well with the measured (target) UPVs. The correlation coefficient was 84.8 percent. The system was able to rank all six specimens in the correct order of deterioration. This investigation demonstrates that the automated interpretation of UPE signals for continuous interfaces by the ANN is feasible.

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